A Simple-Effective Approach for Myoelectric Control of Prosthetic Devices for Rehabilitation

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Abstract— **Myoelectric signals (MES) (a. k. a. Electromyography (EMG) signals) are tried to be utilized in prosthetic control devices. Many problems appeared in controlling more than one device. In this paper, we are first reviewing the problem of using Myoelectric Signals (MES) from the human muscles for controlling a prosthetic robot arm for rehabilitation of patients after stroke, explaining the principles. We proposed a simple approach based on the Euclidean norm of wavelet coefficients as features, were we proved that our technique is very simple and effective were we achieved highly accurate results with error rate of only 0.52%, without even features reduction stage.**
Keywords- **Myoelectric Control, Biomedical Signal Processing, Rehabilitation.**

I. INTRODUCTION

The field of Biosignals research has enjoyed a rapid increase in popularity in the past few years. The Electromyography (EMG) signal, also referred to as the Myoelectric signal (MES), is recorded at the surface of the skin. It is one of the biosignals generated by human body, representing a collection of electrical signals from the muscle fibre, acting as a physical variable of interest since it first appeared in 1940's [1]. It was considered to be the main focus of scientists and was advanced as a natural approach for the control of prosthesis since it is utilising the electrical action potential of the residual limb's muscles remaining in the amputee's stump (which still has normal innervations and thus is subject to voluntary control) as a control signal to the prosthesis, in other words it allows amputees to use the same mental process to control their prosthesis as they had used in controlling their physiological parts, however, the technology in that time was not adequate to make clinical application viable. With the development of semiconductor devices technology, and the associated decrease in device size and power requirements, the clinical applications saw promise, and research and development increased dramatically. The essential elements of a myoelectric control of prosthesis devices are shown in the block diagram schematic of Fig. 1 [2]. The Myoelectric control system is based on the non-invasive interfaces designed for casual wear. ***The noninvasive interfaces***: are those interfaces that *acquire signals transcutaneously, using surface electrodes, which are pre processed to reduce noise content.*

In the following sections, the details and related works to the research problem are given, after that the methodology adopted is explained and discussed, followed by experimental results and finalised with conclusion.

II. BACKGROUND AND RELATED WORK

Continuous myoelectric controlled devices are one of the challenging research issues, in which the prosthetic is controlled in a manner proportional to the level of myoelectric activity. Although the success of fitting these systems for single device control is apparent, the extension to control more than one device has been difficult [3], but, unfortunately, it is required for those with high-level (above the elbow) limb deficiencies, and the individuals who could stand to benefit from a functional replacement of their limbs [4]. It has been proved that the MES signal exhibits a deterministic structure during the initial phase of muscle contraction, as shown in fig. 2 for four types of muscle contractions measured using one surface electrode. Based on this principle a continuous myoelectric control strategy based on the use of pattern classifiers was the main focus during the last years for all scientists, and was clearly investigated by Hudgins [3].

The MES patterns exhibit distinct differences in their temporal waveforms. Within a set of patterns derived from the same contraction, the structure that characterizes the patterns is sufficiently consistent to maintain a visual distinction between different types of contraction. Hudgins [3, 5] aligned the patterns using a cross-correlation technique and showed that the ensemble average of patterns within a class preserves this structure. The myoelectrical signal is essentially a one-dimensional pattern and the methods and algorithms developed for pattern recognition can be applied to its analysis. The myoelectric control system based pattern classifier consists of four broad system components, which are [6, 7] :

- Myoelectric signal acquisition using surface or implanted electrodes, mostly surface electrodes.
- Signal conditioning and features extraction.
- Pattern recognition algorithms to classify the signal into one of multiple classes.
- Mapping of classified patterns to interface actions that control external devices

A general look onto the myoelectric control system components reveal that it operates at a few stages of machine pattern recognition or interpretation for biosignals that were proposed in [6, 7].

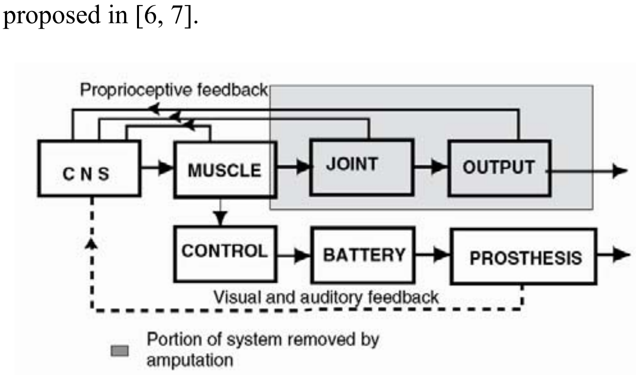

Fig.1 Normal and Myoelectric Control System

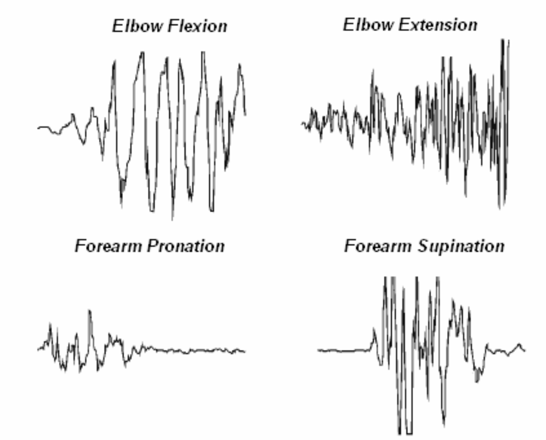

Fig.2. Patterns of transient MES activity Recorded using a single bipolar electrode pair, placed over the biceps *and* triceps.

Also specific features are extracted usually, because the motivation is toward the evaluation of myoelectric signal features in ways which are not tied to accurate estimates of signal characteristics, but rather to the intrinsic quality of the features as control signals for a desired device, which have been usually a prosthetic hand robot for the purpose of rehabilitation.

The increasing of the number of devices under the control of the myoelectric signal, need more sophisticated means of discriminating different muscle states. Two things are needed for this to be possible [8]:

1. More information must be extracted from the MES about the active muscle state. The manner in which one might extract more information from the MES could involve one or both of the following approaches:
   - Use multiple channels of MES, providing localized information at a number of muscles sites, where as to control n functions in the prosthesis requires n unique patterns of muscle contraction.
   - Develop a feature set that extracts as much information as possible from the MES and serves to discriminate different classes of movement.
2. A classifier capable of exploiting this information must be constructed. The role of the classifier is to assimilate and exploit the information it receives, and decide from which class the information originated.

The features extraction is considered as the most important part, because the success of any pattern classification system depends almost entirely on the choice of features used to represent the continuous time waveforms [3]. Although the literature includes many papers which explore the extraction of features from the MES for controlling prosthetic limbs, there have been few works which make quantitative comparison of their quality. Overall, a high quality MES feature space should have the following properties [9]:

- ***Maximum class separability***. A high quality feature space is that which results in clusters that have maximum class separability or minimum overlap. This ensures that the resulting misclassification rate will be as low as possible.
- ***Robustness***. The selected feature space should preserve the cluster separability in a noisy environment as much as possible.
- ***Complexity***. The computational complexity of the features should be kept low so that the related procedure can be implemented with reasonable hardware and in a real-time manner

Raw MES offers us valuable information in a particularly useless form. This information is useful only if it can be quantified. Various signal-processing methods are applied on raw EMG to achieve the accurate and actual MES. Most of the researches on myoelectric control focused on the extraction of features that will best serve the purpose of controlling the prosthetic arm, the first attempts were made since 1980's when Doerschuk [10] and Graupe[11] (that were both based on [12]), used the parameters of some stochastic models such as an autoregressive (AR) model or autoregressive moving average (ARMA) model as features set for the myoelectric control system. Auto-regressive parameters (AR) were used as features for the MES signal [13, 14], as AR parameters can accurately estimate the power spectrum of the signal. It is worth to observe some important advantages of modelling the signal in this way [15]:

- Variations in the positioning of the electrodes on the surface of the muscle do not severely affect the AR-coefficients.
- The amount of information to be presented to the classifier is greatly reduced. Therefore, the total processing time is also reduced.

Recently, all attempts to extract features from the MES can classified in general into two categories [16], although there still many using the AR model for features extraction, and those two categories are:

- ***Temporal Approach***: identifies the attributes of the raw MES signal that characterize its temporal structure relative to a specific muscular function.
- ***Spectral approach***: uses information contained in frequency domain, which leads to a better solution for encoding the MES signal.

It was shown through all the work in literature that the spectral approach results were superior to that of the temporal approach, and that's why we adopted a spectral technique for features extraction.

III. METHODOLOGY

With multi-resolution analysis, fast wavelet transform (FWT) leads to dyadic pyramidal implementation using filter banks and the corresponding Mallat algorithm [17]. FWT develops the two channel filter banks through which the signal is split into two subspaces, L and H, which are

orthonormally complementary to each other, with L being the space that includes the low frequency information about the original signal and H includes the high frequency information. We keep repeating the decomposition of the low frequency subspace L. Compared to FWT, The wavelet packet (WP) method is a generalization of wavelet decomposition that offers a richer range of possibilities for signal analysis. , the wavelet packet transform (WPT) not only decomposes the approximation coefficients, but also the details coefficients H as shown in fig.3 in which, the level of decomposition is to scale index 3.

The WPT provides a selective sub-banding which is the best for a given part of signals selected such as in the case of the MES in which the most signal energy is positioned in between 35Hz – 250 Hz [3, 18]. The selective banding in WPT is determined by the order of low-pass and high-pass filtering from a tree-like structure using these filters [5].

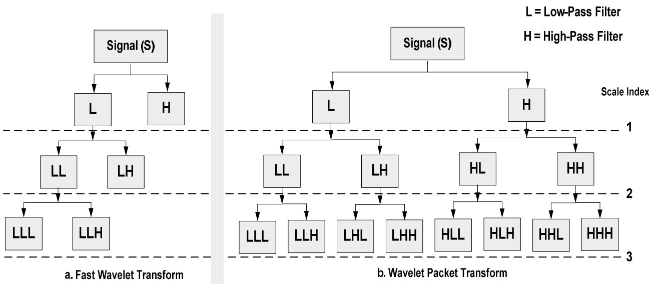

Fig.3 Tree-like structure of digital signal processing by
a) FWT analysis to scale 3
b) WPT analysis to scale index 3.

Our proposed approach uses wavelet packet transform (WPT) for features extraction, with four level of decomposition of the same database that is used by [19] from the San Diego State University (focusing on the synergetic control of groups of finger joints that correspond to the basic prehensile motion), in which The MES signals of the four channels are sampled and recorded as the raw signal data, . There are six categories of grasp types: small cylinder (SC), large cylinder (LC), small ball (SB), large ball (LB), small disk (SD) and a key (SK). Each of the six categories has thirty recorded grasp instances, respectively. There are totally 180 recorded grasp instances and the recorded data are used for feature extraction. Each instance generates a feature vector as the result of feature extraction by the WPT method. Four types of grasps are considered in this database, those are: Cylindrical grasp, Precision grasp, lateral key grasp, and Spherical grasp, as shown in fig4.

The input feature vectors are computed in two simple steps, first each record of the database is decomposed using WPT with the fourth level (using two wavelets families: Daubechies, and Symmlet), secondly features are extracted by simply determining every component of the feature vector ($f_1, f_2, ..., f_N$) using the Euclidean norm.

Assuming the number of nodes in the fourth level is simply N and that each node contains M elements

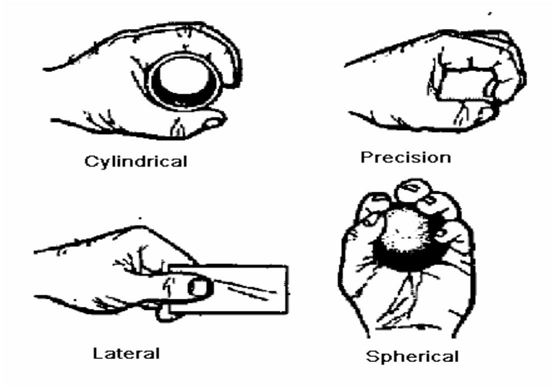

Fig.4 Four grasp types

representing a row vector r_j for $j = 1,2,...,N$ the Euclidean norm is given by:

$$\left[f_j := \left\| r_j \right\|_2 = \sqrt{\sum_{i=1}^{M} v_i^2} \right] \quad .... (1)$$

This means that each feature f_i is determined as the square root of the energy of the wavelet coefficients in the corresponding node, representing time and frequency information of the specific signal. A single feature especially describes a certain frequency range, which is equal to that described by wavelet coefficients underlying this feature. The method of computing the energy of wavelet coefficients was introduced in [20], but they used the FWT instead of WPT.

Because WPT possesses the useful property of identifying distinguishing characteristics from the original signals, we map the original signal into many WPT feature space. The number of valid decompositions increases exponentially with the number of decomposition level, so a problem found here is to compute the optimal decomposition. In our experiment we found that the fourth level was very appropriate to deal with such problem, as further decomposition is not necessary for our work. The number of features selected at the fourth decomposition level was also a matter of our research investigation, were we started with 12 features , and gradually increased the number of features extracted per channel (till 16 feature/channel), to reaching the optimal results. The other part of our system was the classifier, to distinguish the six classes of movements in the database, we simply choose the Linear Discriminant Analysis (LDA), and achieved a high accuracy from the proposed system. The Block diagram of the proposed system for classifying six categories of movements is shown in fig.5, simply containing the extraction of features from the energy of WPT and followed by the LDA classifier.

Our system is different from that proposed by Englehart and his colleagues in [4], were they used records of data each with 256 sample, and later extracted features by WPT, due to the size of their feature vectors they used Principle component analysis to reduce the feature set dimension, and followed that was an LDA part for classification, achieving an average error rate of 0.5% for four classes of motion, and 2% for six classes problem. In our case, we used the records

from San Diego State University (SDSU), each containing 400 sample, and extracted a number of features from the Euclidean norm of wavelet coefficients achieving 64 features for the whole four channels, thus not requiring PCA, and conveyed those to an LDA classifier and the results were very successful, as shown in Table1-1, consisting of the number of features per channel, the error rate, and the wavelet families that we used in our experiments.

IV. Practical Results

We carried out our experimental results, using MATLAB version 7, were we programmed the whole system. It is obvious from the table of experimental results that the case of 16 features per channel for Symmlet family of WPT and Daubechies of WPT gave the best results; also increasing the decomposition level to five gave 100% accuracy for the both families of wavelet. Our design was used to classify six classes of motion achieving error rate of 0.56% using Symmlet family, were as in [4] the six classes problem reached only 2% of error rate.

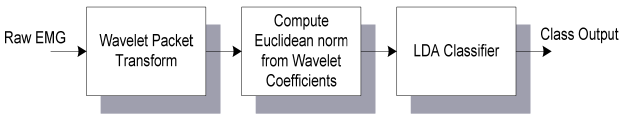

Fig.5 Block diagram of the proposed system.

Features/Channel	Error %	Wavelet
16	0.56%	Symmlet
14	0.56%	Symmlet
12	1.11%	Symmlet
16	0.52%	db4
14	1.67%	db4
12	2.78%	db4

Table-1 Practical Results from our experiment.

V. Conclusion

In this paper, a Simple and very effective Wavelet based approach has been explained for the problem of MES classification for the purpose of rehabilitation of patients after stroke. A simple method of extracting features from the wavelet coefficients was adopted and proven to be very effective in increasing the classification accuracy of the designed system. Although being simple, the accuracy of the classification system reached 99.44% for the case of six classes of motion using the Symmlet family of the order five. The design described in this paper, represented a new promising approach for practical implementation of Myoelectric controlled prosthetics, which we will be further enhancing for the application of real-time controlled prosthesis, were we are currently investigating fuzzy approaches in feature selection as future work.

VI. Acknowledgment

The authors would like to acknowledge the support of Dr. Marko Vuskovic from the San Diego State University, for supplying the database.

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